Firm-specific Human Capital Accumulation: Evidence from Brazil *

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Abstract

We introduce firm-specific returns to experience and tenure into a standard two-way fixed effects model and provide new evidence on heterogeneity of returns to experience and tenure across firms using the administrative matched employer-employee data from Brazil over the years 1999-2014. We find that 1) assuming that employer-employee match quality is determined by firm-specific wage premia and firm-specific returns to experience and seniority, the average return to 5 years of seniority is equal to 14.7%, 2) returns to tenure are not strongly related to firm wage premia (i.e. firm FEs), 3) returns to experience are strongly negatively correlated with firm wage premia, 4) the relationship between firm wage premium and return to experience is stronger for "blue collar" firms.

1 Introduction

There is no reason to believe premia to experience and seniority are the same across firms. For example, firms that offer low entry wages may compensate the workers by offering higher returns to seniority in order to reduce worker turnover. Similarly, firms may reward past experience dif-

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ferently or, alternatively, offer high wage premia irrespective of experience in order to attract most productive workers. Which of these strategies prevails is an empirical question.

Labour economists have long acknowledged heterogeneity in wage premia paid by different firms by including firm fixed effects into panel data wage regressions (see e.g. Abowd et al. (1999) (AKM, henceforth), Card et al. (2013)). However, studies documenting heterogeneity in *return* to experience and tenure are scarce.[1] For example, Dustmann and Meghir (2005) allow for varying returns to tenure and experience across firms and workers but do that within a correlated random coefficients model. They identify and discuss only the mean returns and do not investigate how experience/tenure returns are correlated with firm fixed effects.

We extend the standard two-way fixed effects model by allowing the experience and seniority premia to vary across firms (see Polachek and Kim (1994) for an early effort in introducing individual-specific slope coefficients into panel data regressions). We estimate the model by OLS using the Brazilian matched employer-employee data on large firms ($>$ 100 workers) over the period 1999-2014. The data contains over 11 million workers and over 11 thousand firms, which allows us to estimate heterogeneity across multiple dimensions.

We use the model to document the heterogeneity in returns to experience and tenure and correlation between these returns and other firm-level variables. Our main findings are:

- Returns to experience are strongly inversely related to firm-specific wage premia (i.e. firm fixed effects) whereas this relationship is much weaker for returns to tenure.
- The relationship between firm wage premium and return to experience is stronger for "blue collar" firms (i.e. firms with low average level of education).

These findings, amongst others, confirm that, on average, firms with low wage premia (conditional on all other characteristics and worker fixed effects) compensate workers by rewarding their labour market experience well.

Secondly, we provide new estimates of the return to tenure under the assumption that workers sort themselves across firms based on firm-specific wage premia and firm-specific experience and

[1] AKM allow firm-specific returns to seniority, but keep returns to experience constant across firms. They do not analyse the distribution of returns to seniority across firms in detail. Additionally, their model produces very different mean returns to seniority across different estimation methods (see Table IV in their article). Thanks to recent advancements in computation we can fully solve the least squares problem and do not have to resort to restricted methods as in AKM.

seniority premia. As argued by Topel (1991) simply regressing wages on experience, tenure and fixed effects does not produce unbiased estimates of returns to tenure as workers will sort themselves across firms based on the quality of the employer-employee match. Intuitively, by allowing heterogeneous returns to experience and tenure we control for the part of the match quality coming from differential rewards provided in wage contracts offered by different firms. We estimate the return to 5 years of seniority at 14.7%, which is lower than the estimate in Topel (1991): 17.9%, and Buchinsky et al. (2010): 29%, but higher than the estimate in Altonji and Williams (2005): 9.7%.[2] Additionally, the return to tenure increases compared to the standard model that does not include firm-specific experience and tenure premia, which suggests that controlling for match quality leads to higher estimated returns.

Thirdly, we provide a new decomposition of log wage variance distinguishing the contribution of firm-specific experience/tenure premia. Although there is substantial variation in seniority returns across firms, its contribution to the wage variance is negligible. Also, as the returns to experience are negatively correlated with firm-specific wage premia, heterogeneity acts towards decreasing wage inequality here. Thus, the overall contribution of heterogeneity in experience/tenure returns to wage inequality is small. Other papers performing wage inequality decompositions using two-way fixed effects models include AKM, Card et al. (2013), Song et al. (2018), among others.

We estimate reduced form panel wage regressions. There is a large structural literature that incorporates various forms of heterogeneity in wage returns (see e.g. Belzil and Hansen (2002), Belzil and Hansen (2007), Belzil et al. (2017), and especially Belzil and Hansen (2001)). However, authors in this literature are able to introduce very limited number of "types", usually in single digits, and employ a random coefficients assumption, whereas we estimate separate coefficients for each firm (i.e. more than 10000 coefficients) and allow them to be correlated both with observed characteristics and unobserved ability (worker and firm fixed effects). Of course, we can achieve this flexibility due to the fact that we do not extensively model selectivity as these papers do.

[2]Dustmann and Meghir (2005) estimate 12% for skilled workers and 20% for unskilled workers.

2 Econometric model

We pose the following model for real wages:

$$\log W_{ijt} = \alpha_i + \phi_j + \gamma_j^S Ten_{ijt} + \gamma_j^G Exp_{it} + X_{it}'\beta + u_{ijt} \tag{1}$$

where:

- W_{ijt} - real hourly wage of worker i in firm j at time t
- α_i - worker fixed effect (FE)
- ϕ_j - firm fixed effect
- Ten_{ijt} - tenure of worker i in firm j at time t
- Exp_{it} - experience of worker i at time t
- X_{it} - person-specific control variables, e.g. education

Thus, compared to the standard model (referred in this article as the homogeneous model) we allow the experience and tenure coefficients to vary between firms.

Let $J(i,t)$ denote the function that identifies worker i's employer at time t. Once we control for firm-specific returns to experience and tenure we impose the following exogenous mobility assumption:

Assumption 1 (Exogenous mobility)**.** *We have:*

$$\begin{aligned} E[u_{ijt}|i,t,Ten_{ijt},Exp_{it},X_{it},J(i,t)=j] &= E[u_{ijt}|i,t,Ten_{ijt},Exp_{it},X_{it},J(i,t)=J(i,t-1)=j] \\ &= E[u_{ijt}|i,t,Ten_{ijt},Exp_{it},X_{it},J(i,t)=j \neq J(i,t-1)] = 0 \end{aligned}$$

This assumption implies that in our model the error term u_{ijt} represents market-wide shocks, measurement error etc. and workers do not sort themselves across firms based on u_{ijt}. In particular, the error term has mean zero both for workers staying at the firm ("stayers") and moving to another company ("movers"). Note that this assumption is weaker compared to a corresponding assumption in the homogeneous model as our model already separates differential wage contract terms with respect to experience and tenure premia from u_{ijt}.

2.1 Relation to Topel (1991)

There is an ongoing discussion in the literature about importance of returns to tenure. Whereas authors like Topel (1991), Dustmann and Meghir (2005) and Buchinsky et al. (2010) estimate large returns to tenure, Altonji and Shakotko (1987), Altonji and Williams (2005) argue that tenure is relatively unimportant as a determinant of wages. The main difficulty in estimating returns to tenure is dependence of experience/tenure on participation and job-to-job transition decisions, which in turn are governed by differing employer-employee match quality.

Consider the simple model in Topel (1991):

$$\log W_{ijt} = \gamma^S Ten_{ijt} + \gamma^G Exp_{it} + \epsilon_{ijt}$$

where:

$$\epsilon_{ijt} = \psi_{ijt} + \alpha_i + u_{ijt}$$

and ψ_{ijt} is interpreted as the quality of the match between worker i and firm j at time t. Within this framework our model can be seen as assuming:

$$\psi_{ijt} = (\gamma_j^S - \gamma^S)Ten_{ijt} + (\gamma_j^G - \gamma^G)Exp_{it} + \phi_j$$

Thus, heterogeneity of returns to experience and tenure is implicitly introducing match quality into the regression.

2.2 Identification

We estimate our model by OLS. Thus, identification follows from a standard rank condition on the matrix of observables and fixed effect dummies. In order to gain some more insight into the sources of identification of firm-specific tenure and experience effects (γ_j^S and γ_j^G) we look at wage dynamics among stayers and movers. As identification of β follows from standard arguments, in order to simplify the exposition we focus on the model without X_{it}:

$$\log W_{ijt} = \alpha_i + \phi_j + \gamma_j^S Ten_{ijt} + \gamma_j^G Exp_{it} + u_{ijt}$$

Identification of the model parameters consists of the following steps:

1. Identify $\gamma_j^S + \gamma_j^G$ from wage dynamics among *stayers*:

$$\log \frac{W_{ijt}}{W_{ijt-1}} = \gamma_j^S + \gamma_j^G + u_{ijt} - u_{ijt-1}$$

   as $E[u_{ijt} - u_{ijt-1}|i,t,J(i,t) = J(i,t-1) = j] = 0$ under Assumption 1.

2. Identify γ_j^S from wage dynamics among *movers*:

   - Note that for *movers* from firm j to j' we have:

$$\log \frac{W_{ij't}}{W_{ijt-1}} = \phi_{j'} - \phi_j + \gamma_j^G - \gamma_j^S Ten_{ijt-1} + u_{ij't} - u_{ijt-1} \quad (2)$$

   - Now subtracting the mean across all movers from j to j':

$$\log \frac{W_{ij't}}{W_{ijt-1}} - \frac{1}{TN_{movers}} \sum_{t=1}^{T} \sum_{\text{movers } j \to j'} \log \frac{W_{ij't}}{W_{ijt-1}} =$$
$$= -\gamma_j^S (Ten_{ijt-1} - Ten_{\cdot j \cdot -1}) + u_{ij't} - u_{ijt-1} - (u_{\cdot j' \cdot} - u_{\cdot j \cdot -1}) \quad (3)$$

     which identifies γ_j^S's under Assumption 1.

3. Finally, α_i and ϕ_j can be identified using standard arguments, i.e. we need firms to be "connected" by mobility of workers between them.

Step 2 requires some discussion. Note that equation (3) is trivially satisfied and does not provide any identifying power if there is only one mover from firm j to firm j' over the sample period. On the other hand, the right-hand side of (3) does not depend on j', which implies that in order to identify γ_j^S in practice we need at least two workers moving from company j to *some* company j'. In principle, this restricts us to focus on larger companies.

When it comes to the last step, Jochmans and Weidner (2019) show that precise estimation of worker and firm fixed effects requires good level of mobility between firms, which is captured by measures of global connectivity of the bipartite employer-employee network and the firm network (where connections between firms are formed by job switchers). Appendix A contains analysis of these networks in our RAIS data.

We note that our specification in (1) does not include non-linear terms for experience and tenure. Identification of firm-specific coefficients corresponding to nonlinear terms in experience and tenure would follow similar arguments. With nonlinear terms, step 2 would identify both linear and nonlinear firm-specific coefficients.

3 Data: RAIS

The data used in this paper come from the *Relação Anual de Informações Sociais* (RAIS), a matched employer-employee dataset assembled by the Brazilian Ministry of Labour and Social Security (MTPS). The data is based on yearly reports submitted by firms who are required by law to do so and face fines if they do not. The data contains unique social security identifiers of workers (*PIS*) and firms (*CNPJ*), which allows us to track them over the sample period, 1999-2014.[3]

Our sample includes private sector firms with over 100 workers. We focus on the group of working age males. As job switchers are really important for identifying and estimating the firm-specific coefficients in our model we drop firms with less than 10 job movers over the sample period, which leaves 89% of firms and 98% of workers out of the initial sample. Additionally, we drop all workers with inconsistent entries on education or age within the sample, namely, workers for which we record a drop in years of education or age, which excludes 13.9% of workers in the sample. After scrutinising these cases we conclude that the inconsistencies mainly result from mistakes in entering the data by the companies, in particular recording data under the wrong worker identifier (*PIS*).[4]

Finally, we select the largest connected component of firms network (where edges are formed by worker mobility). As we already focus on large firms with significant mobility the largest component contains 99.5% of firms and more than 99.99% of workers.

[3] See Dix-Carneiro (2014) for a more detailed description of RAIS.

[4] The dropped workers spend, on average, two more years in the panel, are more experienced and come predominantly from large companies. As probability of at least one mistake in the records increases with worker's time in the sample and large companies are more likely to confuse worker identifiers, this suggests that these mistakes are due to data entry errors.

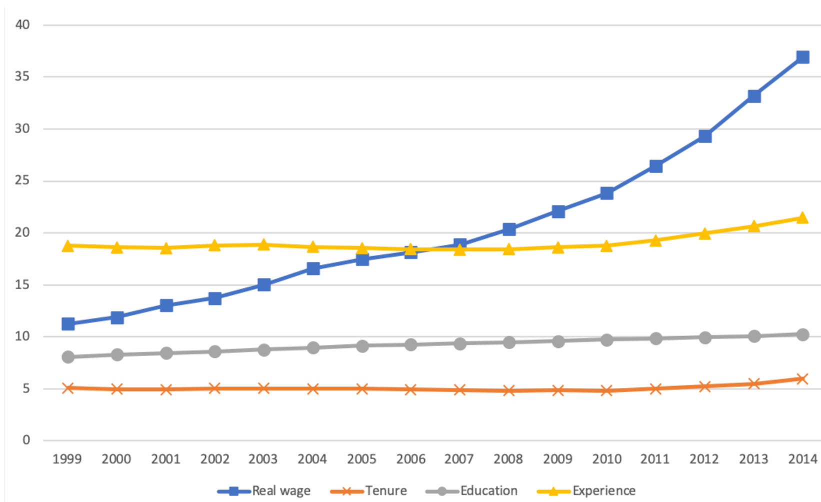
Table 1: Summary statistics

	Mean	Std. Dev.	Min.	Max.
Wage (in 2010 Reals)	21.93	34.68	0.42	1739.82
Tenure (in years)	5.06	6.13	0	45
Experience (in years)	19.08	10.48	0	45
Years of education	9.35	3.26	0	21
NT	64,521,664			
J	11,218			
N	11,679,563			

Note: Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

As we do not observe the full history of employment for each worker we approximate experience by age - years of education - 6. We generate hourly wage by dividing the monthly salary by the number of contracted hours and then deflate the wages using the CPI index. Table 1 contains the summary statistics. Our final sample includes $11,218$ firms and more than 11 million workers. The average wage is equal to 21.9 Brazilian Real, which amounts to approximately \$5 per hour.

Figure 1: Trends in the RAIS data



Note: All data points correspond to averages for a given year. Education is measured by years of completed education.

Figure 1 displays the trends in the data. Brazil experienced dynamic economic growth during 1999-2014, with the real wage tripling in this period. This period also saw a steady rise in the average education level. The average tenure and experience is fairly stable across time, with a slight uptick towards the end of the sample. The latter is caused by the fact that we exclude workers who spent only one year in the panel, which, as a result, excludes young workers entering the job market in 2014 as well as young workers switching in and out of employment in the final years of the sample.

4 Results

We estimate our model by ordinary least squares using the iterative LSMR method of Fong and Saunders (2011). As the model includes many firm-specific coefficients we discuss the fit of the model and the estimates of the common coefficients first and then analyse variation in the firm-specific coefficients.

As mentioned above, our model in (1) does not include nonlinear profile in experience and tenure. This simplifies the exposition of results and implies that the experience and tenure coefficients should be interpreted as linear approximations to the possibly nonlinear profiles. We show in Section 6.1 that including diminishing returns to experience and seniority leads to the same conclusions.

4.1 Coefficient estimates & fit

We compare estimates of our model in (1) to a standard two-way fixed effects model and a model with heterogeneous effect of experience but homogeneous effect of tenure in Table 2.

We estimate a 11% return per year of education across specifications which is in line with other estimates for this region (see e.g. Psacharopoulos and Patrinos (2018)). The standard specification (column (1)) estimates a return to an additional year of experience of 9.8% and a 1.4% yearly return to seniority.

As in other two-way fixed effect studies the models fit the data quite well, explaining around 92% variation in real wages in Brazil. Although including firm-specific returns to experience and/or tenure introduces many new coefficients into the model, it improves the fit to the wage data (see the increase in adjusted R^2).

4.2 Heterogeneous coefficients

Table 3 contains summary statistics of the estimated worker and firm fixed effects and firm-specific experience and tenure coefficients.

Table 2: Results: common coefficients and measures of fit

	(1)	(2)	(3)
Edu	0.112315***	0.112681***	0.112170***
	(2969.063)	(2987.137)	(2943.761)
Exp	0.098232***		
	(6297.673)		
Ten	0.013924***	0.014302***	
	(836.310)	(821.987)	
Worker FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Het. Exp coeff.	No	Yes	Yes
Het. Ten coeff.	No	No	Yes
NT	62,722,307	62,722,307	62,722,307
R^2	0.922	0.924	0.925
Adjusted R^2	0.905	0.908	0.909

Note: t-statistics are given in parentheses. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Table 3: Heterogeneous coefficients

	Mean	Std. Dev.	Corr(·, firm FE)	Corr(·, worker FE)
Worker FE	0.000	0.931	0.041	
Firm FE	0.085	0.311		0.041
Exp	0.098	0.009	−0.453	0.054
Ten	0.020	0.028	−0.099	0.072

Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

The mean return to an additional year of experience is 9.8%, very close to the estimate from the homogeneous model in column (1) of Table 2, whereas the mean return to tenure is 2% per year compared to 1.4% from the homogeneous model. This confirms the observation from previous studies that simply regressing wages on tenure, without controlling for match quality, leads to downward bias in the returns to tenure.

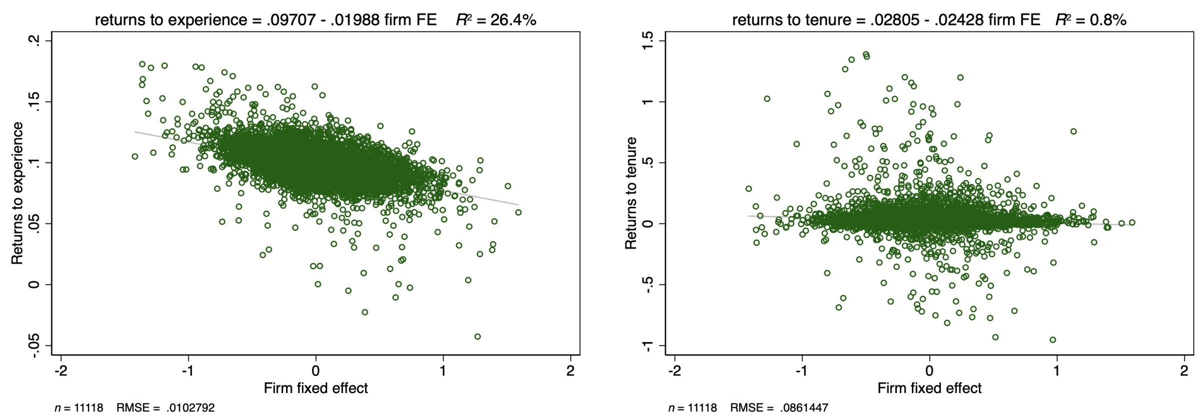
We find much larger variation in returns to tenure (coefficient of variation, CV, equals 1.4) than in returns to experience ($CV = 0.092$) across firms.[5] Thus, we conclude that firms differ significantly in how they remunerate seniority. Last column of Table 3 shows clear evidence of assortative

[5]In what follows we abstract from the estimation error in the estimated worker- and firm-specific parameters. As we argue in Appendix B the correlations we find in the data are unlikely to be driven by the estimation error or small sample bias.

matching between firms and workers, both in terms of more able/productive workers matching with firms with higher starting wage premia ($Corr(\alpha_i, \phi_j) = 0.041$) but also in terms of them matching with firms providing better remuneration for experience and tenure ($Corr(\alpha_i, \gamma_j^G) = 0.054$ and $Corr(\alpha_i, \gamma_j^S) = 0.072$).

Finally, the results in column 3 suggest that the wage contracts (at least in Brazil) compensate high starting wage premia (i.e. high ϕ_j) with lower returns to experience (γ_j^G) and seniority (γ_j^S). This relationship is much more pronounced for experience. This is also illustrated in Figure 2 which shows that firm-specific wage premia explain 26.4% of variation in firm-specific returns to experience whereas they hardly explain any variation in firm-specific seniority premia.[6]

Figure 2: Heterogeneous coefficients: return to experience (left) and tenure (right) versus firm fixed effect



Note: Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1). Outliers are excluded. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Interestingly, Figure 3 shows that returns to experience and tenure are only slightly negatively correlated. Thus, firms who reward initial experience well do not seem to reward well firm tenure at the same time. Other interpretation is that firms who reward general labour market experience well do not really build a lot of firm-specific capital.

Additionally, if we measure the mean quality of workers in a firm by the average worker fixed effect (over workers and time), we can investigate how the experience and tenure premia are related to characteristics of workers. Figure 4 illustrates our findings. The returns to experience do not seem to be related to average worker quality (net of education) at the firm level at all. There is a

[6]We exclude outliers from the figures by dropping bottom and top 0.1% of the observations. The outliers usually correspond to imprecisely estimated effects for firms which spend only a few years in the sample.

slight positive relationship between tenure premia and worker quality but it is not very strong.

Overall, our findings support a view of wage contract setting in which firms differ significantly on how they remunerate loyalty but, in general, they compensate low wage premium (conditional on observed characteristics) with better reward for labour market experience.

4.3 Analysis for subpopulations

In this section we try to shed some light at the regularities detected above by looking at different subpopulations of firms. We focus on the relationship between returns to experience and firm fixed effects as we do not find any clear patterns when looking at returns to tenure.

4.3.1 Differences between industries

One may argue that wage setting mechanisms will vary largely between industries, for example in some sectors the accumulated experience may be of little importance so firms will compete for workers mainly by offering attractive wage premia. Thus, the negative correlation shown in Figure 2 may be fully explained by inter-industry differences.

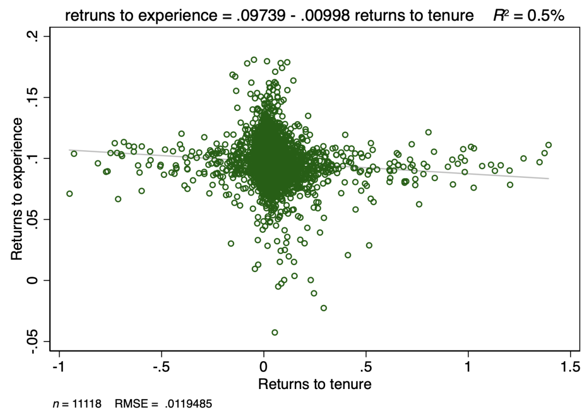
Table 4: Heterogeneous coefficients for two industries

	Mean	**Std. Dev.**	**Corr(·, firm FE)**	**Corr(·, worker FE)**
Panel A. Services				
Worker FE	0.000	0.928	0.048	
Firm FE	0.127	0.294		0.048
Exp	0.093	0.009	−0.430	0.112
Ten	0.016	0.030	−0.157	0.110
Panel B. Production and construction				
Worker FE	0.000	0.936	0.085	
Firm FE	0.120	0.317		0.085
Exp	0.099	0.007	−0.460	−0.043
Ten	0.021	0.024	−0.036	0.034

Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

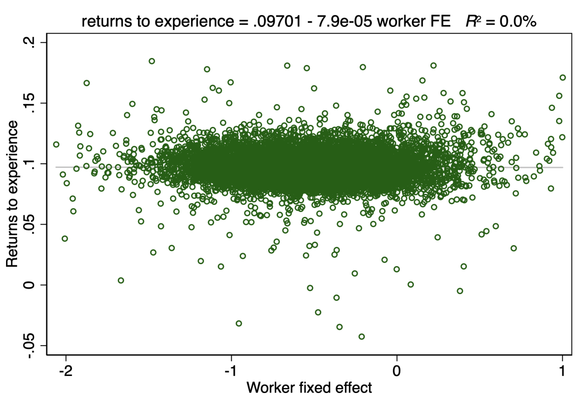
We address this conjecture by looking at correlation between experience premia and firm fixed effects for the services sector and the production and construction sector. Table 4 and Figure 5 illustrate the results.

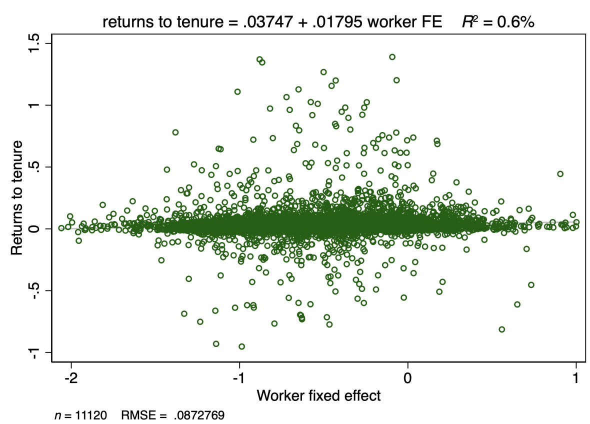
Figure 3: Heterogeneous coefficients: return to experience vs return to tenure



Note: Each point represents a combination of estimated return to tenure and experience from model (1). Outliers are excluded. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

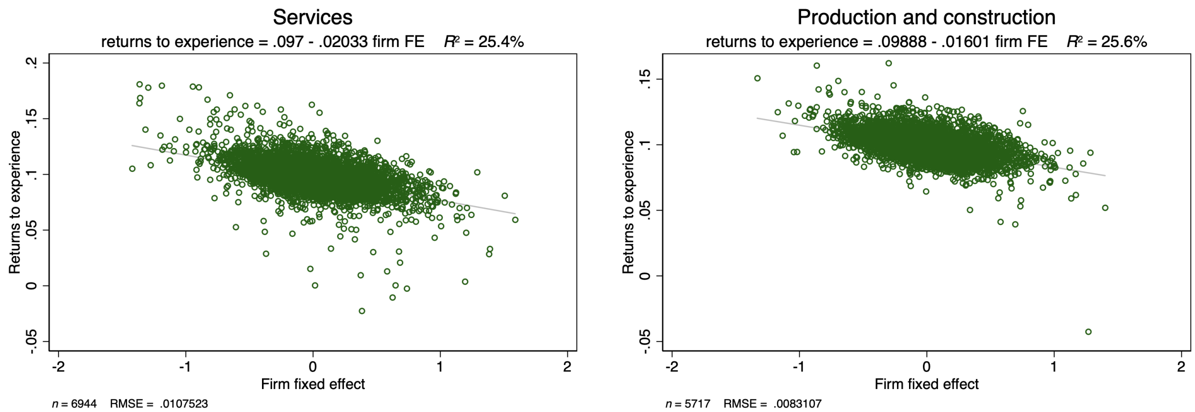
Figure 4: Heterogeneous coefficients: return to experience (left) and tenure (right) versus mean worker fixed effects





Note: Each point represents a combination of estimated return to tenure/experience and average estimated worker fixed effect from model (1). Outliers are excluded. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Figure 5: Returns to experience versus firm fixed effects: industry differences



Note: Each point represents a combination of estimated return to experience and estimated firm fixed effect from model (1). Outliers are excluded. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

The inverse relationship between wage premia and experience returns is present in both sectors and is slightly stronger in the production and construction sector ($Corr(\phi_j, \gamma_j^G) = -0.460$ in comparison to ($Corr(\phi_j, \gamma_j^G) = -0.430$). Overall, inter-industry differences do not seem to explain our findings. If anything, slightly weaker correlation found in the service sector suggests that the relationship may be weaker among firms requiring high skilled labour. We investigate this conjecture in the next section.

4.3.2 Blue collar versus white collar firms

We distinguish "blue collar" and "white collar" firms by the average level of education of their workers. Blue collar firms are companies in the first quartile of the average education distribution and white collar firms correspond to the fourth quartile.

As shown in Table 5, although there is no big difference in mean returns to experience or tenure between the two groups of firms, as expected the average of firm fixed effects is apparently lower for blue collar firms (-0.073) in comparison to white collar firms (0.269). Additionally, the relationship between returns to experience and firm wage premia is stronger for blue collar firms, with the coefficient of determination at 39.5% (see Figure 6). Thus, our results suggest that the apparent substitutability between firm wage premia and experience returns is stronger among low skilled workers ($Corr(\phi_j, \gamma_j^G) = -0.634$). This reflects that jobs with low skill requirements usually

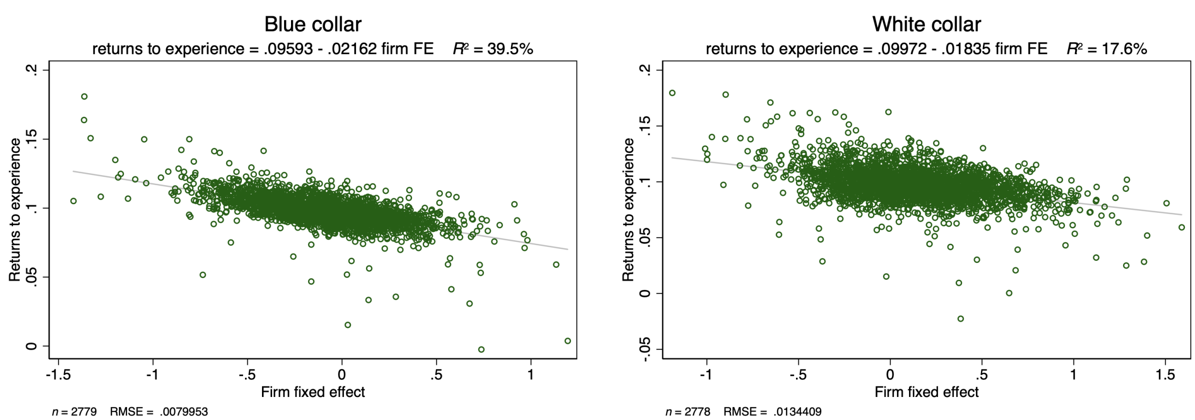
Table 5: Heterogeneous coefficients for blue collar and white collar firms

	Mean	Std. Dev.	Corr(·, firm FE)	Corr(·, worker FE)
		Panel A. Blue collar		
Worker FE	0.000	0.971	0.018	
Firm FE	−0.073	0.260		0.018
Exp	0.099	0.008	−0.634	0.018
Ten	0.017	0.033	−0.067	0.022
		Panel B. White collar		
Worker FE	0.000	0.902	−0.090	
Firm FE	0.269	0.336		−0.090
Exp	0.098	0.010	−0.400	0.038
Ten	0.022	0.029	−0.224	0.068

Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

have a lower initial wage due to the low entry barriers (which manifests itself with low average firm FE), but the wage grows fast with the accumulation of experience and proficiency of skills.

Figure 6: Returns to experience versus firm fixed effects: blue collar (left) and white collar (right) firms



Note: Each point represents a combination of estimated return to experience and estimated firm fixed effect from model (1). Outliers are excluded. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

4.3.3 Differences between small, medium and large firms

With respect to firm size, we divide firms into three groups based on the average level of the number of workers in each firm over the sample period. Small firms are companies with less than

292 workers (1^{st} tercile)[7], and the number of workers in medium firms ranges from 292 to 657 (2^{nd} tercile). For large firms, the number of staff is greater than 657 (3^{rd} tercile).

Table 6: Heterogeneous coefficients: firm size

	Mean	**Std. Dev.**	**Corr(·, firm FE)**	**Corr(·, worker FE)**
		Panel A. Small firms		
Worker FE	0.000	0.939	0.044	
Firm FE	0.004	0.291		0.044
Exp	0.097	0.010	−0.573	0.018
Ten	0.022	0.048	−0.065	0.034
		Panel B. Medium firms		
Worker FE	0.000	0.933	0.037	
Firm FE	0.038	0.281		0.037
Exp	0.097	0.009	−0.506	0.044
Ten	0.021	0.035	−0.090	0.061
		Panel C. Large firms		
Worker FE	0.000	0.927	0.032	
Firm FE	0.105	0.316		0.032
Exp	0.098	0.009	−0.444	0.056
Ten	0.020	0.023	−0.114	0.091

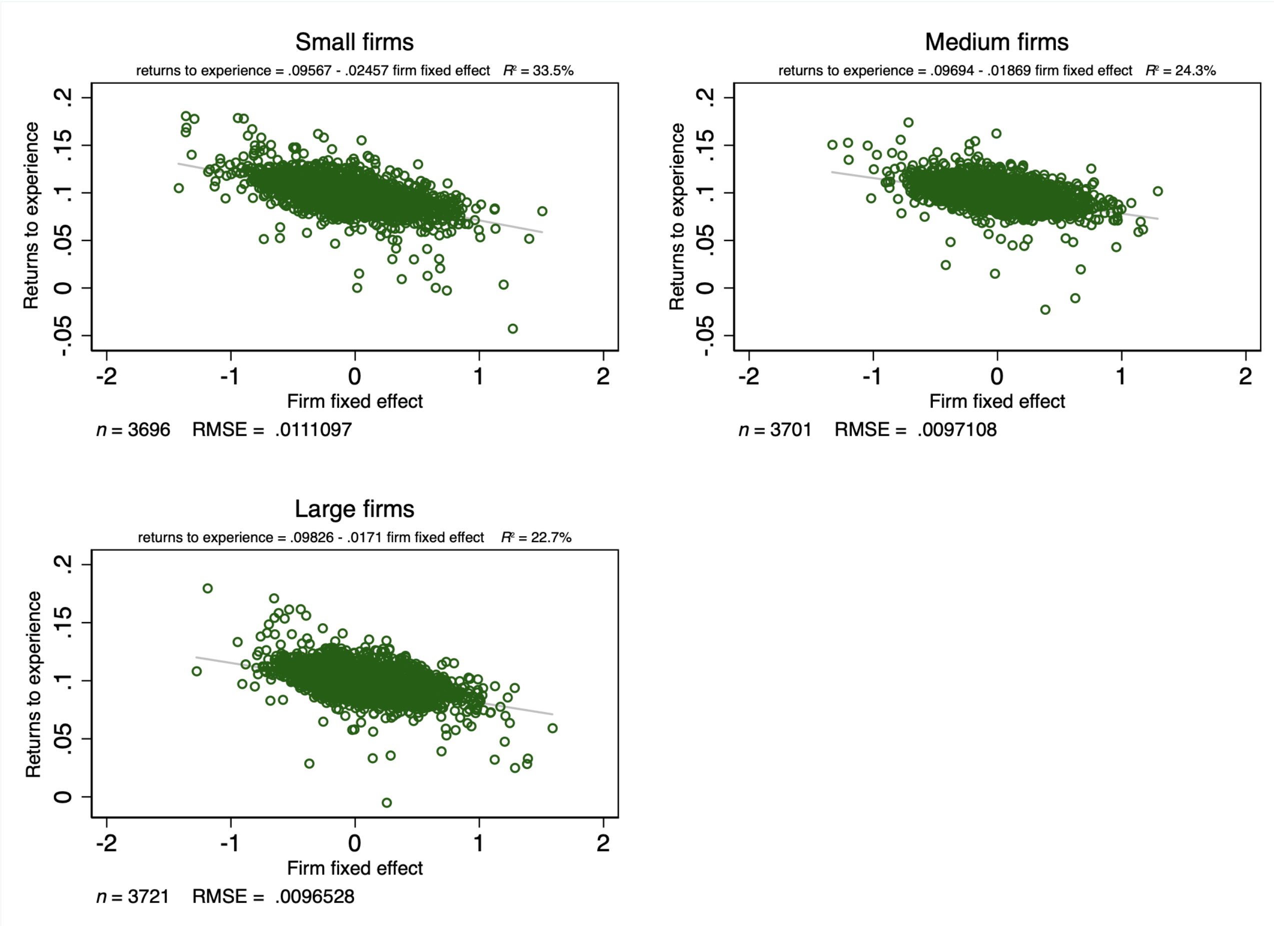
Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Large firms are more capable of providing higher wage premium in wage setting in comparison to smaller firms, thus, as expected, Table 6 shows that large firms offer a much higher average wage premium (0.105) compared to small firms (0.004). However, we see that returns to experience for different firm sizes are very close to each other.[8]

As shown in Figure 7, the negative correlation between returns to experience and firm fixed effects weakens with growing firm size. Variation in firm FE explains 33.5% of variation in returns to experience among small firms compared to 22.7% among largest firms. Thus, among small firms wages of workers starting their jobs in low-pay-premium companies are more likely to catch up with wages of their counterparts starting in high-pay-premium companies, than among larger firms. Though, the differences here are not as stark as between blue- and white-collar firms in Section 4.3.2.

[7]Recall that we restrict our sample to firms employing more than 100 workers.
[8]This may be caused by the fact that we already focus on relatively large companies.

Figure 7: Returns to experience versus firm fixed effects: firm size



Note: Each point represents a combination of estimated return to experience and estimated firm fixed effect from model (1). Outliers are excluded. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

4.3.4 Heterogeneous effects and firm age

Companies with a longer history may be more capable of proving higher wage premium in wage setting in comparison to young firms (see Brown and Medoff (2003) and references therein for a detailed discussion). On the other hand, firms with worse prospects of survival in the market may have to offer higher returns to experience and tenure in order to attract workers and control turnover than more established companies.

We investigate these conjectures by looking at differences in our estimates between young and old companies. As the actual age of firms is unavailable in our data, we use the time spent in the sample as a proxy for firm's age. The median times spent in the sample is 16, which is also the maximum value. Thus, we define old firms as those which are present throughout our sample period 1999-2014 and young firms as the rest.

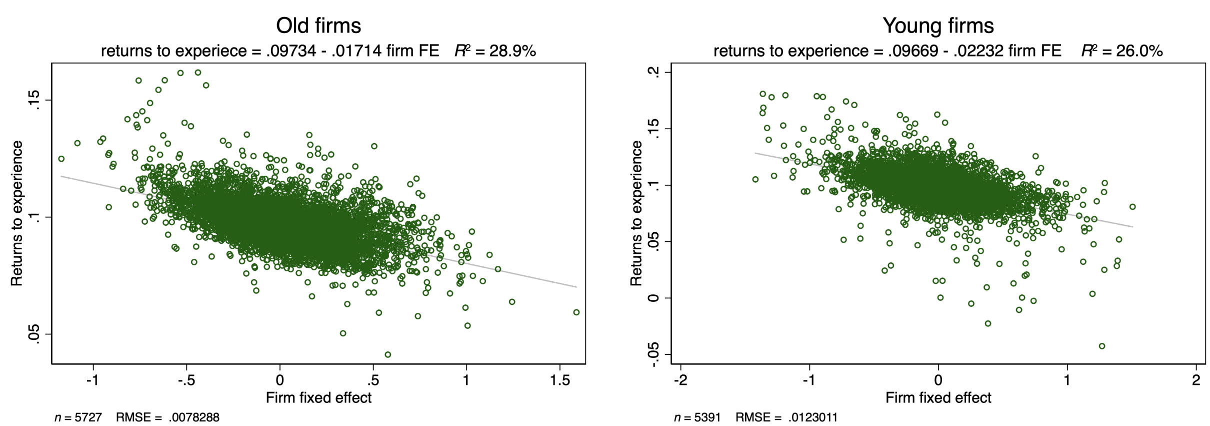
Table 7: Heterogeneous coefficients: firm age

	Mean	**Std. Dev.**	**Corr(·, firm FE)**	**Corr(·, worker FE)**
		Panel A. Old firms		
Worker FE	0.000	0.928	0.037	
Firm FE	0.092	0.316		0.037
Exp	0.098	0.009	−0.481	0.053
Ten	0.019	0.017	−0.155	0.100
		Panel B. Young firms		
Worker FE	0.000	0.937	0.049	
Firm FE	0.067	0.294		0.049
Exp	0.098	0.010	−0.402	0.058
Ten	0.024	0.046	−0.064	0.067

Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Our results in Table 7 confirm the first conjecture, showing that, controlling for worker characteristics and fixed effects, younger firms offer on average lower pay premia (0.067) than old firms (0.098), though the difference is not very large. This result is in line with findings of Davis and Haltiwanger (1991) for the US.

Figure 8: Returns to experience versus firm fixed effects: firm age



Note: Each point represents a combination of estimated return to experience and estimated firm fixed effect from model (1). Outliers are excluded. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Further, Table 7 and Figure 8 show that the negative relationship between wage premium and return to experience is stronger for old companies ($Corr(\phi_j, \gamma_j^G) = -0.481$ and firm FEs explain 28.9% variation in experience returns in this group) but the difference in magnitude is not so apparent. Interestingly, the negative correlation between tenure returns and firm fixed effects is stronger among old firms (-0.155) than young firms (-0.064). If taken at face value, these results would support the "implicit contract" hypothesis behind the relationship between firm age and wages (cf. Baker et al. (1994)) – longer functioning firms can more credibly promise higher wages in the future for working hard now. Thus, they can offer steeper wage profiles compensating initially low wage with large rewards for loyalty to the firm.

5 Variance decompositions

We have shown that there is significant variation in returns to experience and, particularly, tenure across firms. In this section we quantify the contribution of this variation to wage inequality.

5.1 Importance of heterogeneous effects

In the standard model the role of general and firm-specific human capital is associated with the contribution of experience, $\gamma^G Exp_{it}$, and tenure, $\gamma^S Ten_{ijt}$, components to wage variance. As our model allows the returns to experience and tenure to vary across firms, we can further decompose the variation in the experience, $\gamma_j^G Exp_{it}$, and tenure, $\gamma_j^S Ten_{ijt}$, components into between and within firm variation:

$$Var(\gamma_j^S Ten_{ijt}) = \underbrace{Var(E(\gamma_j^S Ten_{ijt}|J(i,t)=j))}_{\text{between firms}} + \underbrace{E(Var(\gamma_j^S Ten_{ijt}|J(i,t)=j))}_{\text{within firms}}$$

and similarly for experience.

Within variation can be associated with variation of worker experience and tenure whereas between variation is related to cross-firm differences in returns to human capital. Table 8 shows that variation in workers experience is the main determinant of the variation in the general human capital in our Brazilian sample with differences in returns to experience playing only a minor role. On the contrary, 45% of variation in the firm-specific human capital can be associated with differences in seniority premia between firms.

Table 8: Human capital variance decomposition: within/between

	$\gamma_j^G \mathbf{Exp_{it}}$	**within**	**between**
var	1.035	0.886	0.152
%	100	85	15
	$\gamma_j^S \mathbf{Ten_{ijt}}$	**within**	**between**
var	0.019	0.011	0.009
%	100	55	45

Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

To sum up, the differences in returns between firms are an important determinant of inequality in specific human capital, whereas they play only a minor role in shaping inequality in general human capital. However, as we are going to see later, variation in returns to tenure play only a minor role in shaping overall wage inequality.

5.2 Wage variance decomposition

Introducing firm-specific returns to experience and tenure changes the specification of the standard model and, thus, leads to different estimates of firm and worker fixed effects and β. As a result this may change the relative importance of firm and worker heterogeneity in shaping wage inequality.

We compare the contribution of different determinants of wages between the standard model and our model using the following log wage variance decomposition:

$$Var(\log W_{ijt}) = \underbrace{Cov(\log W_{ijt}, \alpha_i)}_{worker} + \underbrace{Cov(\log W_{ijt}, \phi_j)}_{firm} + \underbrace{Cov(\log W_{ijt}, \gamma_j^S Ten_{ijt})}_{worker/firm} +$$
$$+ \underbrace{Cov(\log W_{ijt}, \gamma_j^G Exp_{it})}_{worker/firm} + \underbrace{Cov(\log W_{ijt}, X_{it}'\beta)}_{worker} + \underbrace{Cov(\log W_{ijt}, u_{ijt})}_{residual}$$

where we can further decompose:

$$Cov(\log W_{ijt}, \gamma_j^S Ten_{ijt}) = \underbrace{Cov(\log W_{ijt}, \gamma_j^S \overline{Ten})}_{firm} + \underbrace{Cov(\log W_{ijt}, \overline{\gamma^S} Ten_{ijt})}_{worker} + \text{cross terms}$$

and similarly for experience. $\overline{Ten}$ denotes the average tenure in the sample and $\overline{\gamma^S}$ denotes average return to tenure.

Note that we assign each component of the decomposition either to firms or workers. Although this classification seems natural when looking at the contribution of worker and firm fixed effects and contribution of worker-specific observables X_{it}, it is more controversial when it comes to assigning the role of tenure, Ten_{ijt}, and experience, Exp_{it}, as these are not only shaped by workers decisions but also hiring and firing decisions by firms. Introducing this dichotomy, even though somehow artificial, allows us to see if our model changes substantively the discussion about the role of firm and worker heterogeneity in shaping wage inequality.

Table 9: Log wage variance decomposition

	AKM		**Our model**	
	Cov	**%**	**Cov**	**%**
log wage	0.815	100	0.815	100
worker FE	0.224	27	0.222	27
firm FE	0.150	18	0.155	19
Edu	0.164	20	0.164	20
Exp	0.181	22	0.176	22
γ_j^G			-0.007	-1
Exp_{it}			0.180	22
Ten	0.032	4	0.037	5
γ_j^S			-0.001	0
Ten_{ijt}			0.047	6
residual	0.064	8	0.061	7
worker	0.601	74	0.599	75
firm	0.150	18	0.155	18

Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Table 9 shows the contribution of each component in the standard model and in our model. Firstly, note that unobserved worker and firm wage premia explain nearly half of the wage variance in both specifications. Overall, both specifications produce similar decomposition results with our decomposition implying marginally more prominent role for firm-specific capital (row "Ten") compared to general human capital (row "Exp") than the standard model.

It is worth noting that, as anticipated from previous results, heterogeneity in returns to experience works towards decreasing overall wage inequality (row γ_j^G) as low returns to experience compensate high firm-specific wage premia. However, this effect is rather small so the variation in firm-specific experience premia virtually does not contribute to the overall wage variance. Looking at the breakdown between workers and firms (last two rows of Table 9) we notice that our decomposition produces almost exactly the same results as the standard model.

The literature on wage decompositions often takes as a point of interest an alternative decomposition which distinguishes the role of sorting, or generally covariance across regressors, as an important determinant of wage inequality. Results of this decomposition based on our model and data (not reported here) confirm the observations above. Also, in line with the findings from other studies (see e.g. Abowd et al. (1999), Card et al. (2013), Abowd et al. (2019)) we find positive correlation between worker and firm fixed effects which implies positive sorting in the labour market. The value of this correlation in the standard model is 0.07, which is similar to the results found in the aforementioned papers, and decreases to 0.04 in the heterogeneous model. The latter is expected as our model allows for sorting both based on firm-specific wage premia and firm-specific experience/tenure premia.

6 Alternative specifications and robustness checks

6.1 Nonlinear models

As mentioned above, we would normally expect diminishing returns to experience and tenure, thus the standard specification should include nonlinear terms. In this section we add squared and/or cubed experience and tenure to the model and show that our results above are confirmed in this extended model.

The results from the quadratic model and the cubic model are given in Table 10 where we report means and standard deviations of the estimated coefficients as well as mean cumulative returns from 2, 5 and 10 years of experience and tenure. The estimates from the cubic model are highly variable, which suggests that the relatively short length of our panel (16 years) does not allow reliable estimation of higher order curvature of individual experience profiles. This is also confirmed by looking at plots of individual experience profiles (not reported here) with many profiles showing decreasing or explosive patterns. Thus, we focus our discussion on the estimates from the quadratic model which look much more reliable.

The estimates confirm that the returns to tenure are more variable than returns to experience.

Table 10: Heterogeneous coefficients and cumulative returns: nonlinear models

	Mean	**Std. Dev.**	**2 years**	**5 years**	**10 years**
		Panel A. Quadratic model			
Exp	0.130	0.017	0.258	0.633	1.225
Exp^2	-0.001	0.0003			
Ten	0.037	0.061	0.068	0.147	0.215
Ten^2	-0.002	0.093			
		Panel B. Cubic model			
Exp	0.154	0.031	0.300	0.719	1.348
Exp^2	-0.002	0.001			
Exp^3	0.00002	0.00004			
Ten	0.050	0.113	0.090	0.197	0.496
Ten^2	-0.004	0.398			
Ten^3	0.0004	1.406			

Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

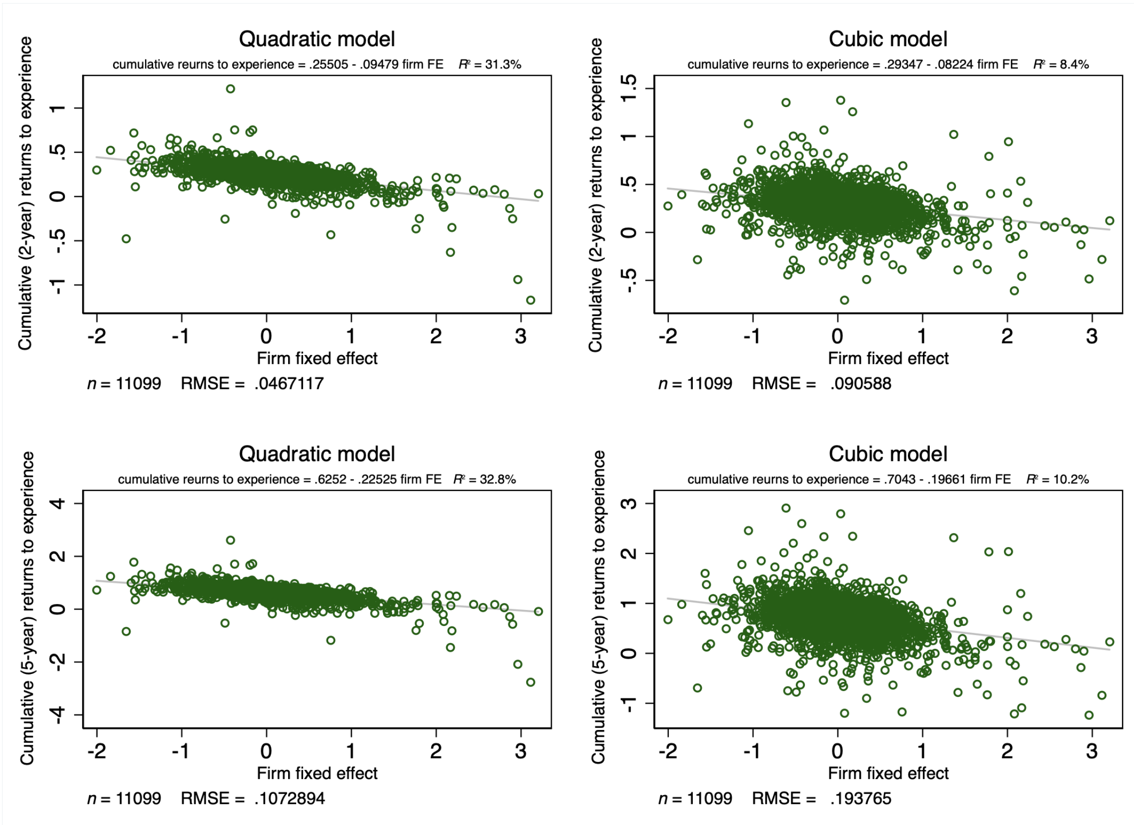
As expected, there are diminishing returns to experience and tenure, with 5 years of tenure yielding a 14.7% return for quadratic model. This is lower than the return found by Topel (1991): 17.9% and Buchinsky et al. (2010): 29%, but higher than the estimate in Altonji and Williams (2005): 9.7%. Dustmann and Meghir (2005) estimate a 12% return to 5 year tenure for skilled workers and 20% return for unskilled labour so our estimate falls in-between.

Our estimate of the return to tenure is higher than the AKM estimate: 7.45%. The AKM does not control for the match quality effect, thus this estimate is likely to be biased. As our model accommodates match quality (see discussion in Section 2.1), this suggests that, in line with the point made in Topel (1991), endogeneity of tenure leads to a downward bias in the estimates of returns to seniority.

Figure 9 shows that the inverse relationship between returns to experience and firm-specific wage premia occurs also in the nonlinear models. The relationship is weaker in the cubic model but, as discussed, we attribute this to imprecision of the cubic estimates due to insufficient length of the panel. Thus, our findings above cannot be explained by misspecification of the linear model in (1).

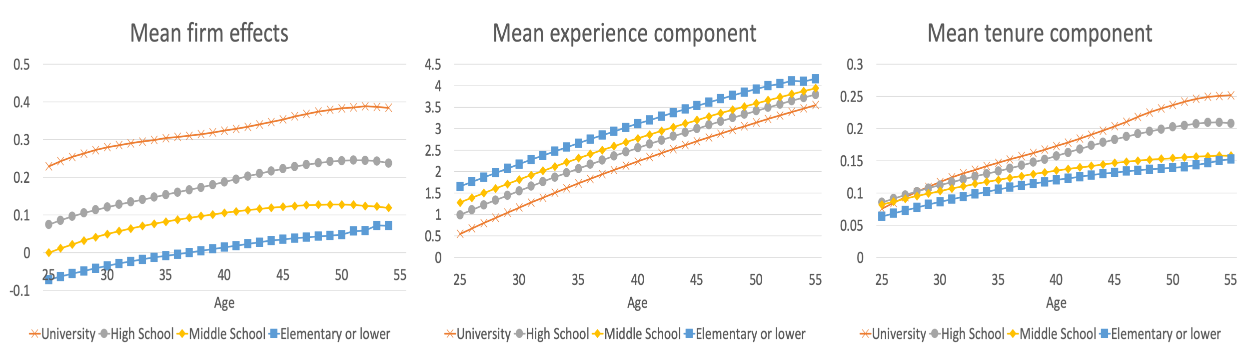
In Figure 10, left panel, we plot mean values of the firm fixed effects by age and education level. We can see that there is positive sorting based on firm wage premia with more educated workers

Figure 9: Cumulative returns to 2 and 5 years of experience vs firm fixed effects: quadratic (left) and cubic (right) model



Note: Each point represents a combination of estimated cumulative return to experience and estimated firm fixed effect from the respective nonlinear model. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Figure 10: Mean fixed effects, mean experience and tenure components by age and education



Note: The mean experience component is calculated as the sample average over $\hat{\gamma}_j^G Exp_{it} + \hat{\gamma}_{j,2}^G Exp_{it}^2$, where $\hat{\gamma}_j^G$ and $\hat{\gamma}_{j,2}^G$ are estimates from the quadratic model. The mean tenure component is calculated similarly. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

working for companies offering higher premia for all age groups. The middle and right panel plot the experience and tenure component of the log wage equation for different age and education groups. As the differences between lines here can be attributed to differences in firm-specific experience premia, the middle panel shows that there is negative sorting of workers on experience premia with more educated workers being employed for companies offering lower returns to experience. This confirms our previous observation that differences in experience premia act towards decreasing wage inequality.

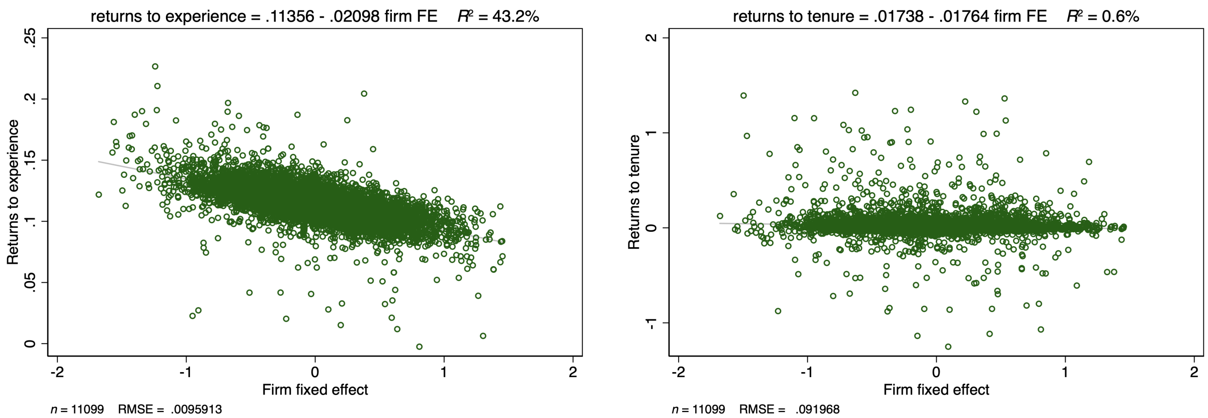
The right panel of Figure 10 shows that the average value of firm-specific human capital is similar across education groups until age 30 but diverges above that age, with educated employees in the age group 50-55 having significantly higher firm-specific human capital component than non-educated employees. Note that in the case of tenure profiles, the differences between the lines cannot be interpreted as only a result of selection based on different firm-specific returns to tenure but can also be caused by different average tenure lengths for educated and non-educated workers. In fact we find that more educated workers have higher average tenure at older ages, which manifests itself with higher value of the specific human capital component ($\hat{\gamma}_j^S Ten_{ijt} + \hat{\gamma}_{j,2}^S Ten_{ijt}^2$) even though the composition of returns to tenure, ($\hat{\gamma}_j^S, \hat{\gamma}_{j,2}^S$), is quite similar in all education groups. Thus, it is the diverging worker histories across education levels, rather than diverging selection patterns, that explain the divergence of profiles in the right panel in Figure 10.

6.2 Actual experience

As mentioned above we use potential experience in our empirical investigation. The rationale is twofold – firstly, we do not observe full worker histories as our data spans years 1999-2014, secondly, as Brazilian labour market includes a large informal sector (see e.g. Dix-Carneiro and Kovak (2019)) we expect that for many workers in our administrative dataset the periods spent outside of the panel correspond to spells of informal employment, thus using potential experience may give a better approximation to actual labour market experience than experience calculated from the RAIS panel.

In this section we investigate the sensitivity of our results to using an approximation to actual experience based on workers histories between 1999-2014. Specifically, we calculate actual experience as $Expact = Exp_0 + Exp_{99-14}$ where Exp_0 is the potential experience (i.e. age - years of education - 6) at the entry to the panel and Exp_{99-14} is the number of years spent in the panel. One way to interpret $Expact$ is that it measures formal sector experience.

Figure 11: Heterogeneous coefficients: returns to actual experience (left) and tenure (right) versus firm fixed effects



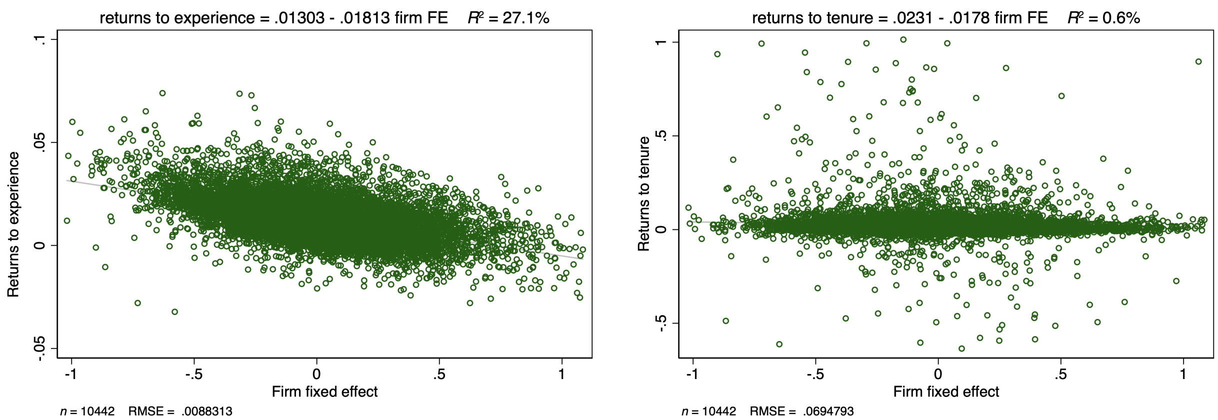
Note: The estimates were obtained using the same methods as the ones in Figure 2. The outliers have been removed from the figures. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

The correlation between potential experience and $Expact$ is quite high, 0.972. Additionally, the model estimates obtained with actual experience are highly correlated with estimates obtained using Exp: correlation coefficient of 0.96-0.97 for worker and firm effects, 0.93 for returns to tenure and 0.86 for returns to experience. Figure 11 shows that, if anything, replacing potential experience with actual experience (or, alternatively, experience in the formal labour market) leads to a slightly stronger inverse relationship between firm-specific returns to experience and firm wage premia. We obtain both slightly steeper line and higher R^2 here than in Figure 2. Also, these results confirm a lack of any visible relationship between returns to tenure and firm wage premia.

6.3 Year fixed effects

As demonstrated in Figure 1, Brazil experienced rapid wage growth during the sample period. In view of that, the strong negative correlation between firm-specific wage premia and experience premia could be seen as a result of mean reversion – firms which pay lower wages initially catch up with the rest during the sample period and this manifests itself with low estimate of firm fixed effect coupled with large estimate of firm's experience premium. Ideally, our model would include year fixed effects in order to control for macroeconomic changes, however, this is not viable as we use potential experience so adding year dummies would create multicollinearity between experience, education and worker fixed effects. However, this ceases to be a problem if we use actual experience, as defined in the previous section.

Figure 12: Heterogeneous coefficients and year fixed effects: returns to experience (left) and tenure (right) versus firm fixed effects



Note: The estimates were obtained using the same methods as the ones in Figure 2. The outliers have been removed from the figures. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Including year effects leads to a correlation between firm fixed effects and returns to experience of -0.5053, which is actually a slightly lower value than in our baseline model. We obtain a very similar correlation of firm FEs with tenure coefficients (-0.089). Also scatterplots in Figure 12 confirm our previous findings. Overall, we conclude that omitting year dummies in our baseline model is unlikely to produce spurious correlation between firm-specific wage premia and firm-specific experience returns due to mean reversion.

6.4 Separate estimates for services and production

The overall firm graph in RAIS is rather weakly connected, with global connectivity measure of 0.02 (see Appendix A). As a result, as argued by Jochmans and Weidner (2019), the firm fixed effects and firm premia may be estimated with little precision. On the other hand, the intra-industry firm graphs are rather well connected with global connectivity of 0.12 for services (still 0.014 measure for production & construction). Thus, as a robustness check to our main results we re-estimate our model separately for service and production & construction sectors.[9]

Table 11: Heterogeneous coefficients: separate estimates for two industries

	Mean	**Std. Dev.**	**Corr(·, firm FE)**	**Corr(·, worker FE)**
		Panel A. Services		
Worker FE	0.000	0.898	0.062	
Firm FE	0.159	0.300		0.062
Exp	0.089	0.010	−0.378	0.136
Ten	0.018	0.041	−0.142	0.067
		Panel B. Production and construction		
Worker FE	0.000	0.948	0.089	
Firm FE	0.094	0.320		0.089
Exp	0.101	0.009	−0.489	−0.042
Ten	0.019	0.028	−0.065	0.036

Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Comparing Table 11 to Table 4 we do not see any stark differences in estimated mean wage returns and correlations between experience/tenure returns and firm fixed effects. If anything, we obtain a slightly weaker correlation between experience returns and firm fixed effects in the service sector (-0.378 versus -0.43 in Table 4) and slightly stronger correlation between returns to tenure and firm fixed effects in the production sector (-0.065 versus -0.036 in Table 4). However, none of these differences is large enough to support the claim that our main estimates are affected by weak connectivity of the employer-employee network. Graphical correlations for both sectors (see Appendix C) also support this conclusion.

6.5 Model without controlling for education

As only one third of workers in our sample changes the education level within the sample period, one may argue that our estimates may be affected by collinearity between education and worker fixed effects for a large group of workers. Thus, in this section we drop education from our model and check the sensitivity of our findings to this alternative specification. In order to make the assumption of non-varying education level credible we focus on workers above 25 years old as most of the workers would finish education by that age.

[9] We choose the largest connected components for each sector. For services this component includes 96% of firms in the sector and 99.9% of workers. For production and construction the corresponding numbers are 99.1% and 99.99%.

Table 12: Heterogeneous coefficients: model without education

	Mean	**Std. Dev.**	**Corr(·, firm FE)**	**Corr(·, worker FE)**
Worker FE	0.000	0.533	0.149	
Firm FE	0.108	0.360		0.149
Exp	0.089	0.011	−0.567	0.112
Ten	0.023	0.029	−0.081	−0.0005

Note: Workers under age 26 excluded. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Table 12 shows no evidence that wage premia, returns to experience and tenure returns for the model without controlling for education are apparently different from corresponding baseline results. Although wage premia (0.108) for the model without controlling for education are slightly higher than the wage premia (0.085) in Table 3, this can be explained by the fact that now firm fixed effects pick up differences in average education levels across firms. Also, the correlation between worker fixed effect and firm fixed effect is much stronger (0.149), nearly three times as in Table 3, as now this correlation indicates assortative matching both on workers individual abilities (i.e. fixed effects) and education.

As can be seen in Appendix C (Figure 14) the relationship between returns to experience or tenure and firm fixed effect is robust to excluding education from the model. Thus, our findings do not seem to be affected by potential collinearity between education and worker fixed effects.

7 Conclusion

We extend the standard two-way fixed effects model of wage formation by allowing the returns to experience and seniority to vary between firms and estimate the parameters using large matched employer-employee dataset from Brazil. We provide new estimates of return to seniority assuming that employer-employee match quality is determined by firm-specific wage premia and firm-specific returns to experience and seniority, obtaining an average return to 5 years of seniority equal to 14.7%. We document the variation in firm-specific experience and tenure premia and find that: 1) returns to tenure are not strongly related to firm wage premia (i.e. firm FEs), 2) returns to experience are strongly negatively correlated with firm wage premia, 3) the relationship between firm wage premium and return to experience is stronger for "blue collar" firms.

As argued by Dustmann and Meghir (2005) transitions in and out of employment and sorting of workers based on match quality, in general, lead to endogeneity of experience in the standard model. Thus, they recommend to identify the effect of experience by using only displaced workers. As RAIS data allows us to track the firms over time and lists the reason for termination of the employment relationship we could potentially identify displaced workers in our data.

Moreover, we define seniority as the time spent with a current employer. However, as shown by Buhai et al. (2014) not only nominal tenure matters for wages but seniority *relative* to other workers is also an important determinant of pay. It would be interesting to investigate heterogeneity in relative seniority using our data. We leave both these extension for future research.

A Connectivity of employer-employee network in RAIS

As recommended by Jochmans and Weidner (2019) we measure connectivity by the smallest non-zero eigenvalue of the (normalized) Laplacian matrix of the graph. We consider both the bipartite employer-employee network and the firm network, i.e. projection of the bipartite network on firm nodes, and distinguish services and production and construction sectors.

Table 13: Smallest non-zero eigenvalue of the normalized Laplacian matrix

	bipartite	firm
all	0.000617	0.019733
services	0.000479	0.116439
production and construction	0.000156	0.014386

Table 13 shows, in line with observations for other matched employer-employee datasets, that the bipartite network is rather weakly connected and contains bottlenecks that will prevent precise estimation of the worker effects. As we do not really use individual effects in our analysis, but rather their firm averages, this weak connectivity is not of major concern. The firm network is much better connected, especially if we restrict ourselves to sectoral sub-networks. The latter suggests that the firm fixed effects and firm-specific coefficients may be estimated with much better precision if we perform within-sector estimation.

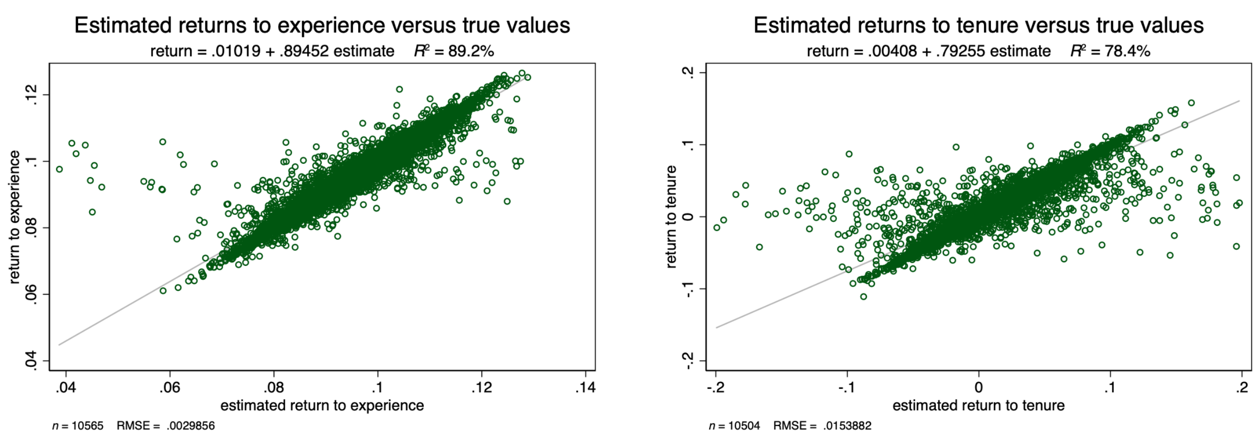
B Role of estimation error

Although our sample contains millions of observations, the firm effects as well as the firm-specific experience and tenure coefficients are subject to estimation error. The estimation error in these coefficients will usually be correlated so this may partly drive our results. In order to appreciate this point, ignore the worker fixed effects and tenure coefficients and consider a highly stylised environment in which all firms share the same value of the fixed effect and the effect of experience. Additionally, assume that each firm's workforce is an independent sample drawn from the population of all workers. In such an environment, we can obtain an estimate of the fixed effect (i.e. a constant term) and the return to experience for each firm by running firm-specific regressions. These coefficients for different firms can be seen as different draws from the sampling distribution of the estimators. Thus, the correlation between the *estimated* firm fixed effects and the *estimated* returns to experience will merely pick up the correlation between the estimators, and will be non-zero even though the correlation between the *true* fixed effects and the *true* returns to experience is zero.

Although our setup is far from this stylised environment, it may still be that the significant correlation between firm wage premia and firm-specific returns to experience are driven partly by the estimation error. In order to investigate this possibility, we perform a simple exercise in which we generate artificial wages using our data and our estimates of the worker fixed effects, the return to education and the sample variance of the residuals. However, instead of the estimated firm-specific experience and tenure premia we use randomly generated numbers from a normal distribution keeping the same mean and variance of the estimates.

Figure 13: Estimates with randomly generated firm-specific returns to experience and tenure

	Mean	**Std. Dev.**	**Corr(·, firm FE)**	**Corr(·, worker FE)**
worker FE	0.000	0.937	0.040	
firm FE	0.084	0.311		0.040
Exp	0.096	0.009	-0.012	-0.004
Ten	0.019	0.034	-0.003	-0.007



Note: The estimates were obtained using the same methods as the ones in Table 3. The data on wages was generated assuming that firm-specific experience and tenure effects are drawn independently from normal distributions with the same means and standard variations as those in Table 3. The outliers have been removed from the figures.

Figure 13 shows that estimating the model on the artificial data produces correlations between the estimated returns to experience and tenure and fixed effects that are close to zero in line with our imposed randomness of the firm-specific coefficients. This suggests that the correlated estimation error plays a minor, if any, role in generating sizeable correlations in our RAIS data (cf. Table 3). Additionally, our exercise reveals that the experience coefficients are likely to be estimated with more precision than the tenure coefficients.

Finally, as the correlations and regression slopes between firm-specific fixed effects and returns are nonlinear functions of the estimates, they may suffer from nonlinearity bias. There has been some recent work on performing estimation and inference on quadratic forms of such coefficients, e.g. variances and correlations, see Kline et al. (2020). In their application they show that their bias-corrected variance decompositions show slightly lower contribution of firms to wage inequality and significantly stronger correlation between worker and firm fixed effects. Having this in mind, we do not expect our results to be dramatically affected by the estimation error in the worker-/firm-specific effects and, if anything we would expect the detected correlations to be biased towards zero. Let us also note that, although the theoretical results in Kline et al. (2020) apply to covariances between firm fixed effects and returns to experience/tenure, practical application of their results is difficult in our setup with numerous estimated regression slopes.

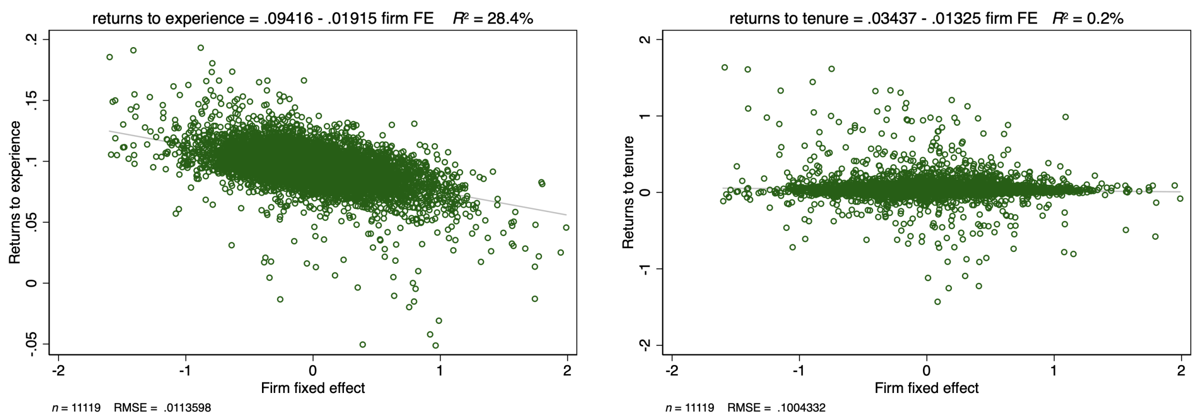
C Additional graphs and tables

Table 14: Summary statistics for subpopulations

	Mean	Std. Dev.	Min.	Max.
Panel A. Service				
Wage (in 2010 Reals)	20.41	32.56	0.42	1739.82
Tenure (in years)	4.72	5.63	0	45
Experience (in years)	19.94	10.44	0	45
Years of education	9.59	3.11	0	21
NT	19,682,990			
J	6,987			
N	3,960,797			
Panel B. Production and construction				
Wage (in 2010 Reals)	25.01	37.95	0.42	1557.26
Tenure (in years)	5.77	6.75	0	45
Experience (in years)	19.51	10.38	0	45
Years of education	9.11	3.48	0	21
NT	32,145,912			
J	5,722			
N	5,792,124			
Panel C. White collar firms				
Wage (in 2010 Reals)	38.41	51.11	0.42	1739.82
Tenure (in years)	6.79	7.68	0	45
Experience (in years)	20.4	11.2	0	45
Years of education	11.49	2.44	0	21
NT	19,522,089			
J	2,805			
N	3,734,432			
Panel D. Blue collar firms				
Wage (in 2010 Reals)	12.11	17.88	0.42	1739.82
Tenure (in years)	6.80	7.68	0	45
Experience (in years)	17.34	9.99	0	45
Years of education	6.43	3.44	0	21
NT	12,660,505			
J	2,805			
N	6,906,558			
Panel E. Small firms				
Wage (in 2010 Reals)	16.18	25.84	0.42	1421.83
Tenure (in years)	4.69	5.26	0	45
Experience (in years)	19.80	10.64	0	45
Years of education	8.80	3.21	0	21
NT	5,427,844			
J	3,728			
N	1,798,672			
Panel F. Medium firms				
Wage (in 2010 Reals)	17.87	27.78	0.42	1491.46
Tenure (in years)	4.67	5.35	0	45
Experience (in years)	19.50	10.57	0	45
Years of education	9.05	3.13	0	21
NT	10,382,180			
J	3,728			
N	3,404,645			
Panel G. Large firms				
Wage (in 2010 Reals)	23.44	36.68	0.42	1739.82
Tenure (in years)	5.19	6.37	0	45
Experience (in years)	18.92	10.43	0	45
Years of education	9.48	3.28	0	21
NT	48,711,640			
J	3,733			
N	9,814,992			
Panel H. Young firms				
Wage (in 2010 Reals)	19.53	29.18	0.4	1708.96
Tenure (in years)	4.51	5.68	0	45
Experience (in years)	19.25	10.54	0	45
Years of education	9.16	3.23	0	21
NT	17,572,016			
J	5,728			
N	4,734,904			
Panel I. Old firms				
Wage (in 2010 Reals)	22.83	36.48	0.4	1739.82
Tenure (in years)	5.27	6.28	0	45
Experience (in years)	19.02	10.45	0	45
Years of education	9.42	3.26	0	21
NT	46,949,648			
J	5,490			
N	9,113,628			

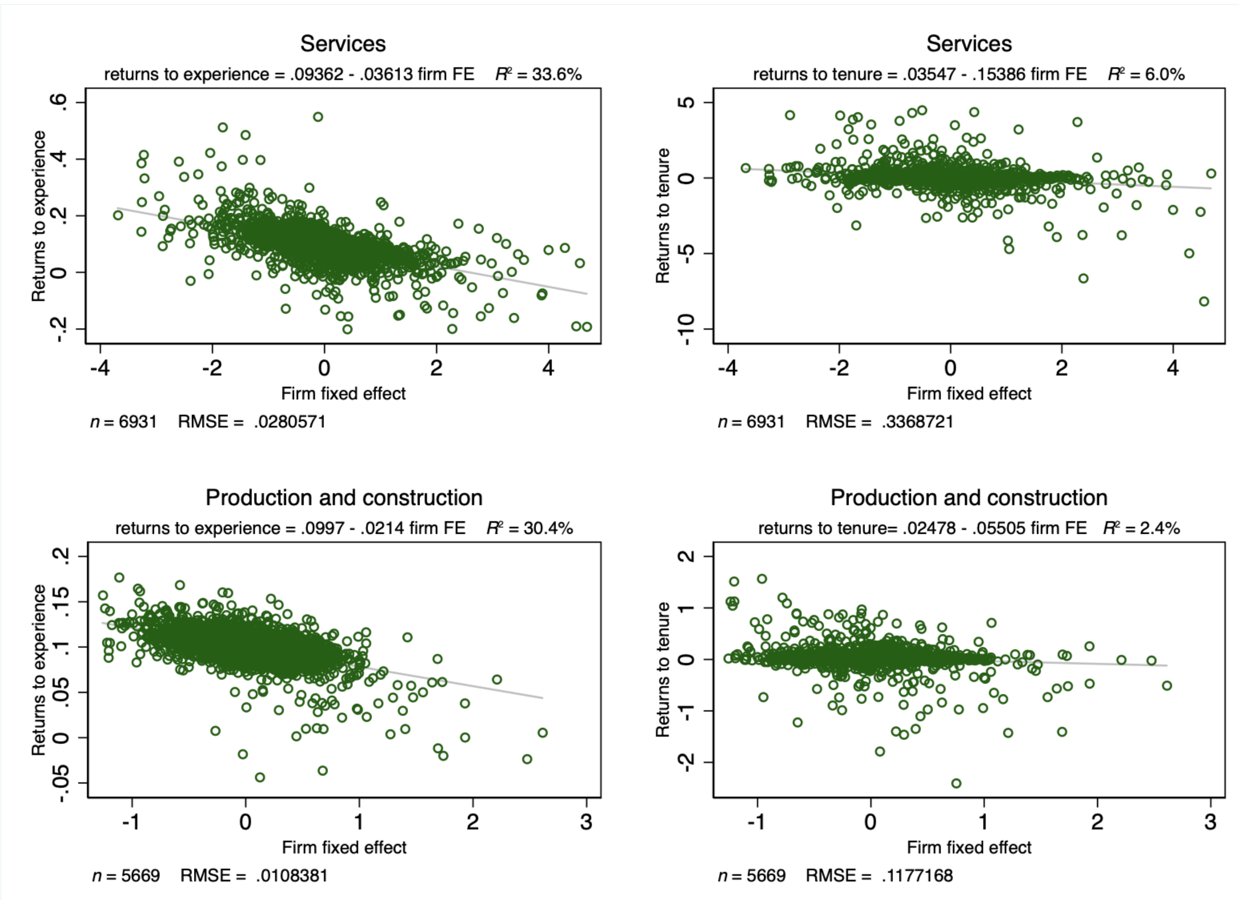
Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Figure 14: Returns to experience (left) and tenure (right) versus firm fixed effects: model without education



Note: Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from the model without controlling for education. Outliers are excluded. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

Figure 15: Returns to experience/tenure vs firm fixed effects: separate estimates for two industries



Note: Each point represents a combination of estimated return to tenure/experience and estimated firm fixed effect from model (1). Outliers are excluded. Data source: *Relação Anual de Informações Sociais* (RAIS) 1999-2014.

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